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(54) **THREE-DIMENSIONAL DISPLAY OF DOCUMENT SET**

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Related U.S. Application Data

(63) Continuation of application No. 09/235,463, filed on Jan. 22, 1999, now abandoned, which is a continuation of application No. 08/695,455, filed on Aug. 12, 1996, now abandoned.

(51) **Int. Cl.**[7] **G06K 9/60**; G06F 17/30; H04N 1/00

(52) **U.S. Cl.** **382/305**; 707/1; 358/403

(58) **Field of Search** 382/306, 305, 382/309, 307, 185; 707/530, 531–538, 2–6, 1, 102, 100; 358/403

(56) **References Cited**

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(57) **ABSTRACT**

A method for spatializing text content for enhanced visual browsing and analysis. The invention is applied to large text document corpora such as digital libraries, regulations and procedures, archived reports, and the like. The text content from these sources may be transformed to a spatial representation that preserves informational characteristics from the documents. The three-dimensional representation may then be visually browsed and analyzed in ways that avoid language processing and that reduce the analysts' effort.

1 Claim, 4 Drawing Sheets

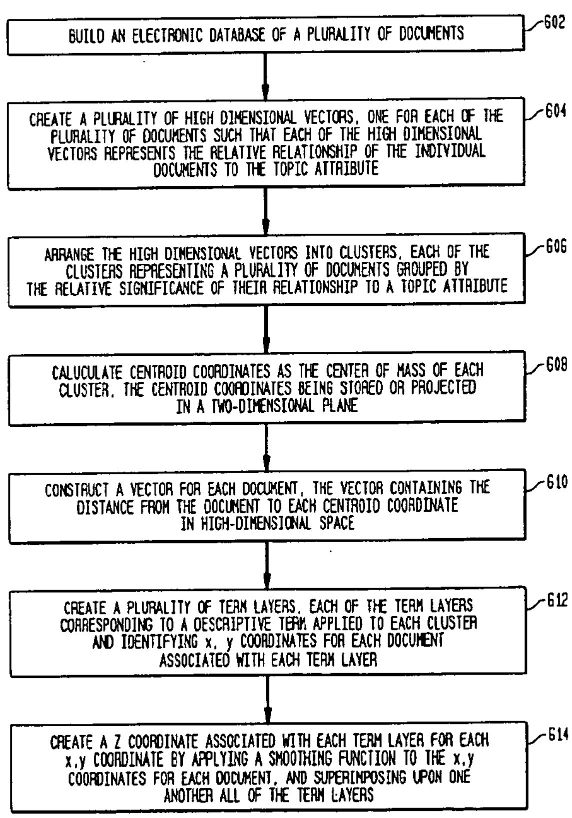


FIG. 1

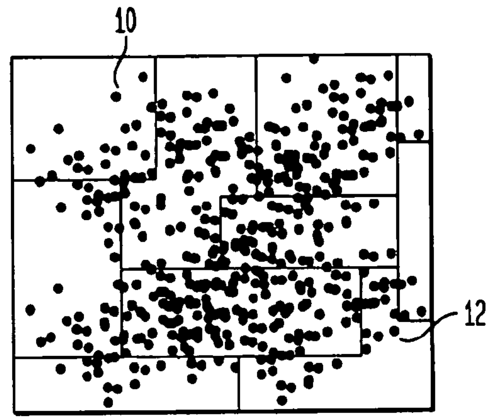


FIG. 2

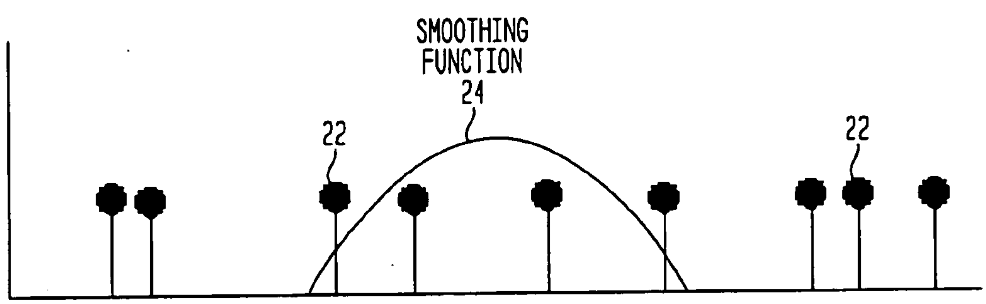


FIG. 3

FIG. 4

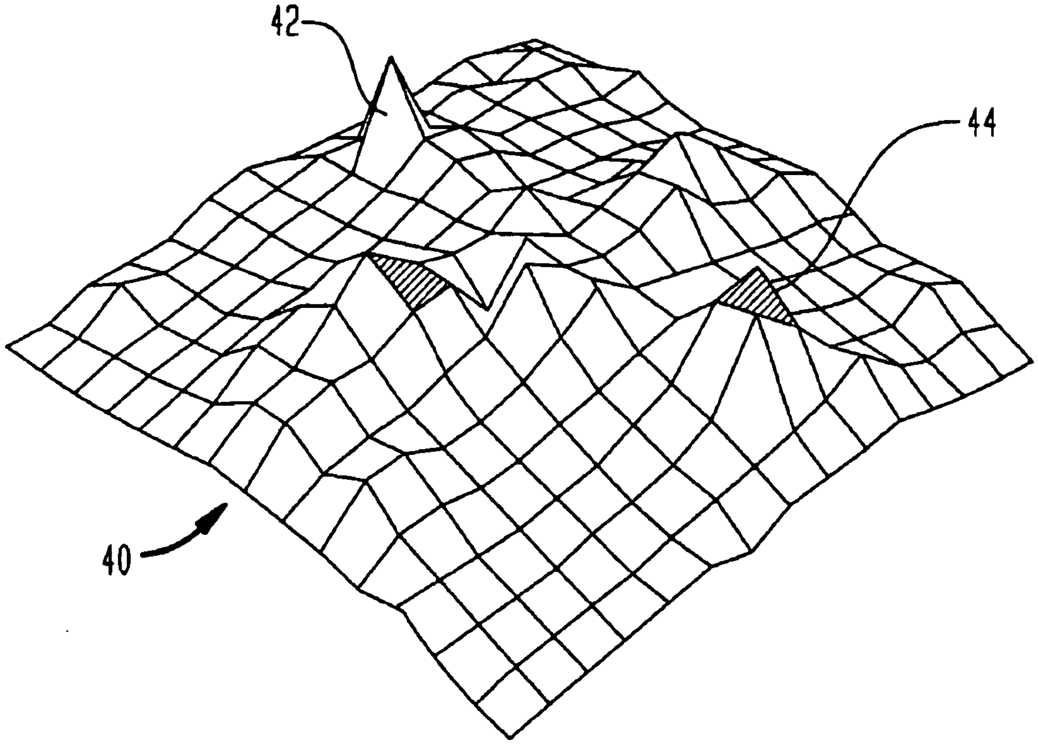


FIG. 5

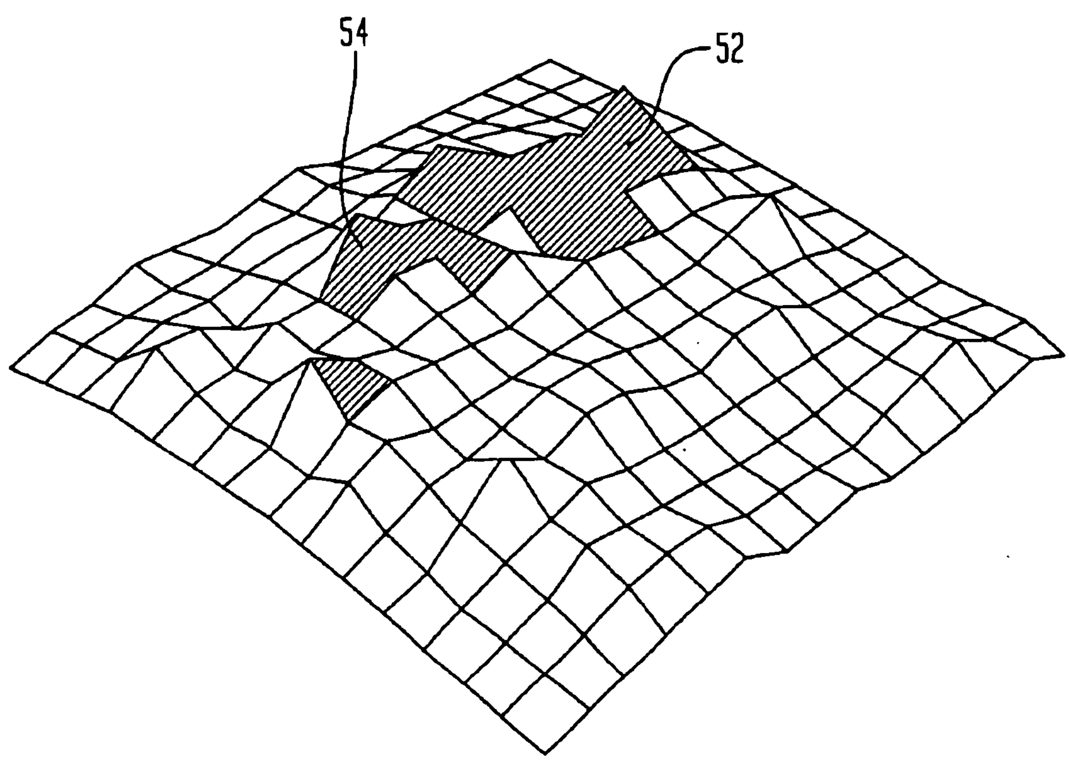
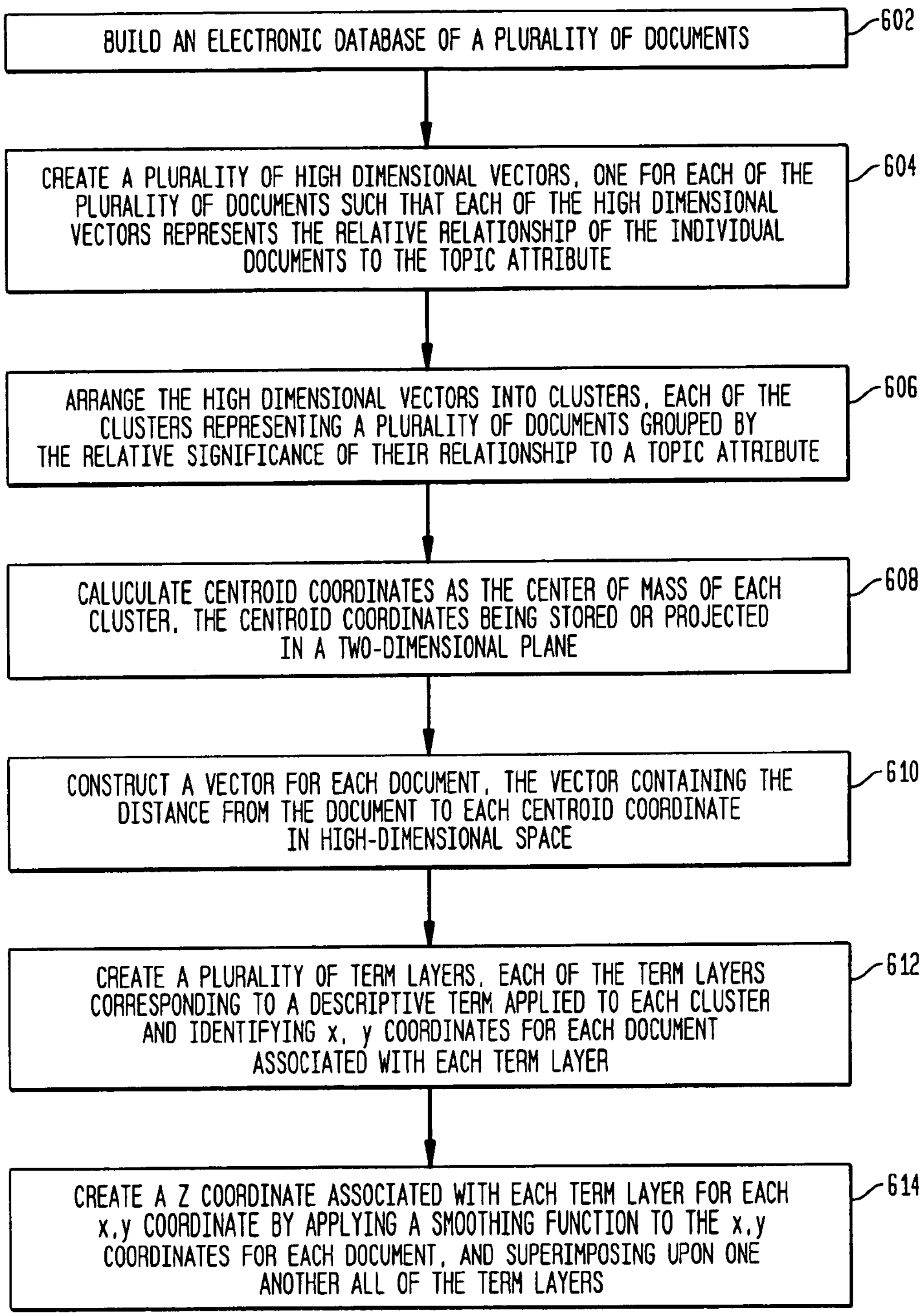


FIG. 6


BUILD AN ELECTRONIC DATABASE OF A PLURALITY OF DOCUMENTS
602
CREATE A PLURALITY OF HIGH DIMENSIONAL VECTORS, ONE FOR EACH OF THE PLURALITY OF DOCUMENTS SUCH THAT EACH OF THE HIGH DIMENSIONAL VECTORS REPRESENTS THE RELATIVE RELATIONSHIP OF THE INDIVIDUAL DOCUMENTS TO THE TOPIC ATTRIBUTE
604
ARRANGE THE HIGH DIMENSIONAL VECTORS INTO CLUSTERS, EACH OF THE CLUSTERS REPRESENTING A PLURALITY OF DOCUMENTS GROUPED BY THE RELATIVE SIGNIFICANCE OF THEIR RELATIONSHIP TO A TOPIC ATTRIBUTE
606
CALUCULATE CENTROID COORDINATES AS THE CENTER OF MASS OF EACH CLUSTER, THE CENTROID COORDINATES BEING STORED OR PROJECTED IN A TWO-DIMENSIONAL PLANE
608
CONSTRUCT A VECTOR FOR EACH DOCUMENT, THE VECTOR CONTAINING THE DISTANCE FROM THE DOCUMENT TO EACH CENTROID COORDINATE IN HIGH-DIMENSIONAL SPACE
610
CREATE A PLURALITY OF TERM LAYERS, EACH OF THE TERM LAYERS CORRESPONDING TO A DESCRIPTIVE TERM APPLIED TO EACH CLUSTER AND IDENTIFYING x, y COORDINATES FOR EACH DOCUMENT ASSOCIATED WITH EACH TERM LAYER
612
CREATE A Z COORDINATE ASSOCIATED WITH EACH TERM LAYER FOR EACH x,y COORDINATE BY APPLYING A SMOOTHING FUNCTION TO THE x,y COORDINATES FOR EACH DOCUMENT, AND SUPERIMPOSING UPON ONE ANOTHER ALL OF THE TERM LAYERS
614

THREE-DIMENSIONAL DISPLAY OF DOCUMENT SET

REFERENCE TO RELATED APPLICATION

This application is a continuation of application Ser. No. 09/235,463 filed on Jan. 22, 1999, now abandoned which is a continuation of application Ser. No. 08/695,455 filed on Aug. 12, 1996, now abandoned and which are hereby incorporated by reference in their entirety.

This invention was made with Government support under Contract DE-AC06 76RLO 1830 awarded by the U.S. Department of Energy. The Government has certain rights in the invention.

FIELD OF THE INVENTION

This invention relates generally to the field of information storage and retrieval, or "information visualization". More particularly, the invention relates to a novel method for text-based information retrieval and analysis through the creation of a visual representation for complex, symbolic information. This invention also relates to a method of stored information analysis that (i) requires no human pre-structuring of the problem (ii) is subject to independent, (iii) is adaptable to multi-media information, and (iv) is constructed on a framework of visual presentation and human interaction.

DESCRIPTION OF THE PRIOR ART

Current visualization approaches demonstrate effective methods for visualizing mostly structured and/or hierarchical information such as organization charts, directories, entity-attribute relationships, and the like. Mechanisms to permit free text visualizations have not yet been perfected. The idea that open text fields themselves or raw prose might be candidates for information visualization is novel. The need to read and assess large amounts of text that is retrieved through graph theory or figural displays as "visual query" tools on document bases puts severe limits on the amount of text information that can be processed by any analyst for any purpose. At the same time, the amount of "open source" digital information is increasing exponentially. Whether it be for market analysis, global environmental assessment, international law enforcement or intelligence for national security, the analyst task is to peruse large amounts of data to detect and recognize informational 'patterns' and pattern irregularities across the various sources.

True text visualizations that would overcome these time and attentional constraints must represent textual content and meaning to the analyst without them having to read it in the manner that text normally requires. These visualizations would instead result from a content abstraction and spatialization of the original text document that would transform it into a new visual representation conveying information by image instead of prose.

Prior researchers have attempted to create systems for analysis of large text-based information data bases. Such systems have been built on Boolean queries, document lists and time consuming human involvement in sorting, editing and structuring. The simplification of Boolean function expressions is a particularly well-known example of prior systems. For example, in U.S. Pat. No. 5,465,308, a method and apparatus for pattern recognition utilizes a neural network to recognize two dimensional input images which are sufficiently similar to a database of previously stored two dimensional images. Images are first image processed and

subjected to a Fourier transform which yields a power spectrum. An in-class to out-of-class study is performed on a typical collection of images in order to determine the most discriminatory regions of the Fourier transform. Feature vectors are input to a neural network, and a query feature vector is applied to the neural network to result in an output vector, which is subjected to statistical analysis to determine if a sufficiently high confidence level exists to indicate that a successful identification has been made.

SUMMARY OF THE INVENTION

The SPIRE (Spatial Paradigm for Information Retrieval and Exploration) software supports text-based information retrieval and analysis through the creation of a visual representation for complex, symbolic information. A primary goal of SPIRE is to provide a fundamentally new visual method for the analysis of large quantities of information. This method of analysis involves information retrieval, characterization and examination, accomplished without human pre-structuring of the problem or pre-sorting of the information to be analyzed. The process produces a visual representation of results.

More specifically, the novel process provides a method of determining and displaying the relative content and context of a number of related documents in a large document set. The relationships of a plurality of documents are presented in a three-dimensional landscape with the relative size and height of a peak in the three-dimensional landscape representing the relative significance of the relationship of a topic, or term, and the individual document in the document set. The steps of the process are:

(a) constructing an electronic database of a plurality of documents to be analyzed;

(b) creating a plurality of high dimensional vectors, one for each of the plurality of documents, such that each of the high dimensional vectors represents the relative relationship of the individual documents to the term, or topic attribute;

(c) arranging the high dimensional vectors into clusters, with each of the clusters representing a plurality of documents grouped by relative significance of their relationship to a topic attribute;

(d) calculating centroid coordinates as the center of mass of each cluster, the centroid coordinates being stored or projected in a two-dimensional plane;

(e) constructing a vector for each document, with each vector containing the distance from the document to each centroid coordinate in high-dimensional space;

(f) creating a plurality of term (or topic) layers, each of the term layers corresponding to a descriptive term (or topic) applied to each cluster, and identifying x,y coordinates for each document associated with each term layer; and

(g) creating a z coordinate associated with each term layer for each x,y coordinate by applying a smoothing function to the x,y coordinates for each document, and superimposing upon one another all of the term layers.

BRIEF DESCRIPTION OF THE DRAWINGS

The accompanying drawings, which are incorporated in and constitute a part of the specification, illustrate preferred embodiments of the invention, and together with the description, serve to explain the principles of the invention.

FIG. 1 is a graphical representation of database relationships in two-dimensional space;

FIG. 2 is a one dimensional representation of documents represented in FIG. 1;

FIG. 3 is a smoothed version of the representation of FIG. 2;

FIG. 4 is a three-dimensional representation of a database having small theme sets and high discrimination; and

FIG. 5 is a three-dimensional representation of a database having large theme sets and low discrimination.

FIG. 6 is a block diagram presenting the sequence step in the preferred embodiment of the present invention.

DETAILED DESCRIPTION OF THE INVENTION

As used herein, the following terms shall have the following definitions:

1. Information Retrieval means access and discovery of stored information. It requires the efficient retrieval of relevant information from ill-structured natural language-based documents. The effectiveness of a retrieval method is measured by both precision, or the proportion of relevant to non-relevant documents identified, and recall, or the percentage of relevant documents identified.

2. Information analysis is discovery and synthesis of stored information. It involves the detection of information patterns and trends and the construction of inferences concerning these patterns and trends which produce knowledge.

The present invention is known as SPIRE (Spatial Paradigm for Information Retrieval and Exploration). SPIRE is a method of presenting information by relative relationships of content and context—that is, the "relatedness" of a plurality of documents to one another both by their sheer numbers and by their subject matter. It is comprised of a plurality of elements which define it's usefulness as an information analysis tool. Briefly, the elements are: a combination of an intuitive and attractive interface, well integrated with a powerful set of analytical tools; a computationally efficient approach to both clustering and projection, essential for large document sets; a three-dimensional visualization component to render stored information in a three-dimensional format (known as ThemeScapes); and a unique interplay between the 2-dimensional and 3-dimensional visualization components.

An essential first step in the transformation of natural language text to a visual form is to extract and structure information about the text—through a "text processing engine". A text processing engine for information visualization requires: (1) the identification and extraction of essential descriptors or text features, (2) the efficient and flexible representation of documents in terms of these text features, and (3) subsequent support for information retrieval and visualization. There are a number of acceptable text engines currently available on the market or as research prototypes, such as the Hecht Nielson Corporation's MatchPlus or the National Security Agency's Acquaintance.

The parameters typically measured by a text engine fall into one of three general types. First, 'frequency-based measures' on words, utilizing only first order statistics. The presence and count of unique words in a document identifies those words as a feature set. The second type of feature is based on higher order statistics taken on the words or letter strings. Here, the occurrence, frequency, and context of individual words are used to characterize a set of explicit or implicitly defined word classes. The third type of text feature is semantic—the association between words is not defined through analysis of the word corpus, as with statistical features, but is defined a priori using knowledge of the language. Semantic approaches may utilize natural or quasi-natural language understanding algorithms.

The second requirement of the text engine (efficient and flexible representation of textual information) is satisfied if identified text features are used as a shorthand representation of the original document. Instead of complex and unwieldy strings of words, feature sets are the basis of document representation. Volume reduction of information is required to make later computations possible

Finally, the text engine must provide easy, intuitive access to the information contained within the corpus of documents through retrieval and visualization. To provide efficient retrieval, the text processing engine must pre-process documents and efficiently implement an indexing scheme for individual words or letter strings. Information retrieval implies a query mechanism to support it—often a basic Boolean search, or a high level query language, or the visual manipulation of spatialized text objects in a display.

The process of the present invention can best be described with reference to a five-stage text visualization process.

STAGE ONE The receipt of electronic versions of textual documents into the text engine described above is essentially independent of, but a required precursor for, the SPIRE process. The documents are input as unprocessed documents—no key wording, no topic extraction, no pre-defined structure is necessary. In fact, the algorithms used to create a spatial representation of the documents presupposes the characteristics of natural language communication so that highly structured information (e.g. tables and outlines) cannot be adequately processed and will result in diminished results.

STAGE TWO The analysis of natural language documents provides a characterization of the documents based on content. Performed in the text engine, the analysis can be first order (word counts and/or natural language understanding heuristics) or higher order information captured by Bayesian or neural nets. The required output is that each document must be converted to a high dimensional vector. A metric on the vector space, such as a Euclidean distance measure or cosine measure, can be used to determine the similarity of any two documents in the collection. The output of this processing stage is a high dimensional vector for each document in the collection.

STAGE THREE The document vectors must be grouped in the high dimensional metric space—"clustering". In order to satisfy performance requirements for large document sets, clustering algorithms with a lower order of complexity are essential. The output of this stage is a partition set on the document collection with measures for each cluster of magnitude (count) dispersion. While it is believed that there are a number of different approaches to the clustering of information that will lead to acceptable results, Applicants have determined to limit the document vectors to "large" (more than 3,000 documents) and "small" (less than 3,000 documents) data sets. For small data sets, readily available clustering algorithms have been used, with primary emphasis on k-means and complete linkage hierarchical clustering.

For larger data sets, traditional clustering algorithms can not be used because of the exponential complexity of the clustering algorithms as the data set increases. Applicants have therefore devised an alternative method for clustering in large problem sets known as "Fast Divisive Clustering". In this process, the user selects the desired number of clusters. No assistance is provided in selecting this number, but it should be heuristically based on knowledge of the data set, such as size, diversity, etc. After the number of seeds has been selected, the next step is to place seeds in the multi-dimensional document space. A sampling of the subspaces is performed to ensure that there is a reasonable distribution of the cluster seeds—that is, they are not too close to one another. Then, the hyperspheres are defined around each cluster seed and assigned to all documents within a hypersphere to the corresponding cluster. Iteratively, the center of mass is calculated yielding a new cluster centroid, and therefore a new location for the hypersphere and new document assignments. Within a few iterations, locations for the cluster centroids will be determined, and the final document to cluster assignments are made. Changes in distances between iterations should remain within a predefined threshold.

This third stage can be summarized as:

(i) selecting the number of seeds, based on characteristics of the document collection;

(ii) placing seeds in hyperspace by sampling regions to ensure reasonable distribution of seeds;

(iii) identifying non-overlapping hyperspheres (one for each cluster) and assigning each document to a cluster based on which hypersphere the document is located within;

(iv) calculating a centroid coordinate—the center of the mass for each cluster; and

(v) repeating steps (iii) and (iv) until centroid movement is less than a prescribed threshold.

STAGE FOUR This stage requires the projection of the high dimensional document vectors and the cluster centroids produced in Stage 3 into a 2-dimensional representation (FIG. 1), The 2-D planar representation of the documents and clusters is necessary for user viewing and interaction. Because the number of dimensions is reduced from hundreds to two, a significant loss of information naturally results. Some representational anomalies are produced by projection, causing documents to be placed with an associated error. The nature and quantity of this error are defining characteristics of the chosen projection. As with the clustering stage, compute time is important for large document sets. Therefore, projection algorithms which are of a low order of complexity are vital. The product of this stage is a set of 2D coordinates, one coordinate pair **(10,12)** for each document.

As with the clustering of Stage three, multiple options for projection techniques are available. For relatively small data sets, Applicants have chosen to use "Multi-dimensional Scaling Algorithm", or MDS. The MDS utilized pairwise distances (Euclidean or cosine angle) between all document pairs. The algorithm attempts to reserve the distances determined in the high-dimensional space when projecting to 2D space. In doing so, the discrepancy between pairwise distances in the high dimensional space and the 2D counterparts are represented as an error measure. The algorithm iteratively adjusts document positions in the 2D plane in order to minimize the associated error. The distance from every point to every other point is considered and weighed against a preset desired distance. Every point influences every other point, making MDS a computationally intensive algorithm.

For larger data sets, MDS is impractical due to the exponential order of complexity, and Applicants have therefore developed a projection algorithm called "Anchored Least Stress". When starting with a fixed number of points (cluster centroids which have been calculated in stage three), the algorithm considers only the distance from a point to the various cluster centriods, not the distance to every other point. The document is placed so that its position reflects its similarity or dissimilarity to every cluster centroid. Only a relatively small amount of initial calculation is required; after that each document can be positioned using simple matrix operations, with a computational complexity on the order of the number of cluster centroids. With the centroids placed in the 2D plane, a vector is constructed for each document which contains the distances from the document to each cluster centroid in the high dimensional space. Given the vector of hyperspace distances, a closed form solution can be constructed which rapidly produces the 2D coordinates of each document in the document collection.

More specifically, if one begins with n cluster centroids cj (the 2-dimensional projection of the cluster centroids from high-dimensional space), assume the coordinate system is such that the center of mass of all the cluster centroids is at the origin. Let

$$c_{\cdot 1} = \frac{1}{n}\sum_{j=1}^{n} c_{j1}; \quad c_{\cdot 2} = \frac{1}{n}\sum_{j=1}^{n} c_{j2} \qquad [1]$$

and then change the coordinates of the centroids as follows:

$$c_{j1}(new)=c_{j1}(old)-c_{\cdot 1};\ c_{j2}(new)=c_{j2}(old)-c_{\cdot 2} \qquad [2]$$

The squared distance between each document i and each of the cluster centroids j (as measured in the original high-dimensional space) is d_{ij}. There are m documents with unknown 2-dimensional coordinates x_i. For each document i and cluster j, we desire to have x_i, such that

$$d_{ij}=\|x_i-c_j\|^2 \qquad [3]$$

The average distance between the document and the centroids

$$d_{i\cdot} = \frac{1}{n}\sum_{j=1}^{n} d_{ij} \qquad [4]$$

and w_{ij} is the unknown quantity

$$w_{ij}=x_i\cdot c_j=x_{i1}c_{j1}+x_{i2}c_{j2} \qquad [5]$$

If it is desired to force documents to be closer to the centroid of the cluster to which they belong, a weighted least squares approach may be utilized. Let w_c be an input weight—this is interpreted as the distance of a point from its own cluster centroid and is w_c times more important than its distance from any other cluster. A matrix S_j is defined to have 0's on the off-diagonal and 1's on the diagonal, except for the (j,j) th entry, which is equal to w_c. The weighted solution for the position of the ith document, when that document is a member of the jth cluster, will be

$$\hat{x}_i=(C^TS_jC)^{-1}C^TS_jY_i \qquad [6]$$

The fourth stage can be summarized as:

(i) performing an anchored least stress analysis on cluster centroid coordinates in hyperspace;

(ii) producing a vector for each document with distance measures from the document to each cluster centroid; and

(iii) constructing an operator matrix and multiply matrix by each vector in step (ii) to produce two-dimensional coordinates for each document.

STAGE FIVE The output of Stage four (a coordinate pair for each document and cluster centroid) is displayed in a scatter plot yielding what Applicants call the "Galaxies" two-dimensional visualization. For this two-dimensional visualization, no further computation of the Stage Four results is required. A three-dimensional representation of the Stage Four results does require further computation, and results in what Applicant calls a thematic landscape, or "ThemeScapes". This 3D representation provides an intuitive visual measure and a spatial position in display space for dominant topics in a corpus of unstructured documents.

ThemeScapes solves the two most troublesome problems encountered with two-dimensional textual information analysis. That is, important subjects of the database are not easily or accurately discernable—the major topics are imprecisely displayed, if provided at all, and are not spatially organized to support the spatial organization of the 2D document display. Secondly, documents are not readily associated with the main topics which they contain. Similarity between documents is conveyed through proximity, but the relationship between documents and topics are indeterminate. How close a particular document is associated with a topic or how a pair of documents are topically related are difficult or impossible to determine.

First, identification of regional topics, or terms, and the set of documents which contain them must be identified. The gisting features of the text engine will identify the major topics of a corpus of documents. While commercially available text engines provide the gisting feature, such text engines fail to provide a local, spatial representation of the theme, a composite measure of theme, a quantitative measure of theme or document by document measure of theme. A clustering of the n-dimensional document vectors (produced in stage three clustering) will result, and the clusters 10 are projected into 2D space so that each document has an assigned x,y coordinate pair, as illustrated in FIG. 1. For each of these clusters, a set of terms which are both "topical" in nature, as measured by serial clustering, and maximally discriminating between clusters, as measured by the product of the frequency of the term within the documents of a particular cluster and the frequency of the term in all other. The general form of the topic equation is

$$\text{term value}_{n,1}=f_{term\ n/cluster\ 1}*1/\Sigma_j f_{term\ n/cluster\ j} \quad [7]$$

with

f term n/cluster I=frequency of term n in cluster I

Σf term n/cluster j=frequency of term n in all other clusters

and the highest value topics are selected.

The terms derived using this equation are the terms which best discriminate clusters from one another. A number of terms or topics for each cluster are automatically and heuristically selected, with topic value, frequency, cluster size, desired number of terms per cluster and per document collection all considered in the selection process. Each term or topic layer represents the distributed contribution of a single term/topic to the surface elevation of a "theme scape". Topic layer thickness may vary over the area of the simulated landscape based on the probability of finding a specified term within a document at each two dimensional coordinate. After all the individual layers have been computed, a composite layer is derived by summing each of the term layers. A topic layer is thickest where the density of documents that contain that term are highest. In areas where there are few documents or few documents that contain a given term, the topic layer is very thin. High ground on the theme scape represents regions where there is an alignment of terms in underlying documents—or a common theme among proximal documents. Regions that are lower and less pronounced reflect documents that are more general in their content and less focused on a single theme.

Each region or cluster is then characterized by a set of terms or topics. Associated with each topic for each cluster is a document set. The document set is nothing more than the result of a Boolean query with the topic as the keyword. The first stage of ThemeScape construction is complete when both regional topics and their corresponding document sets are identified.

The second stage of ThemeScapes development, formation of the three-dimensional surface for individual topics identified above requires a smoothing filter be run over the x,y coordinates of the document display. This process is analogous to operations such as edge detection or feature enhancement in image processing. As illustrated in FIGS. 2 and 3, individual points 22 along the x-axis indicate the location of a document in the topic's document set. A smoothing function is run across each point creating a z coordinate associated with the term layer for each x,y pair, represented as surface 24 above the x-axis. The equation for calculating the y coordinate corresponding to each x coordinate will be of the form

$$y_x=\Sigma_{n=-m}^{n=+m}d_{x+n}*f(x+n), \quad [8]$$

with

$d_{x+n}=1$ for document present at coordinate x+n, else 0

f(x+n) the value of the smoothing function at x_n

2m=width of the smoothing function centered about x.

The two dimensional calculation of a ThemeScape as illustrated in FIG. 3 utilizes a two dimensional grid of documents and a two dimensional smoothing function, producing a third dimension reflecting the probability of finding a document with the given topic in the given vicinity.

Finally, all individual topic ThemeScapes are superpositioned. The individual elevations from each term layer are added together to form a single terrain corresponding to all topics, Thus,

$$z_{x,y} = \sum_{j=1}^{\#\ of\ cluster\ terms} \text{term layer } j_{x,y} \quad [9]$$

Generally, normalization of the above equation is performed.

The result of this computation is a "landscape" that conveys large quantities of relevant information. The terrain simultaneously communicates the primary themes of an arbitrarily large collection of documents and a measure of their relative magnitude. Spatial relationships defined by the landscape reveal the intricate interconnection of themes, the existence of information gaps or negative information. For example, FIG. 4 illustrates a "theme scape" 40 of a database with 200 documents and 50 themes. In this data set, themes had relatively small document sets (a low number of documents contained in each theme), but high theme discrimination values (the documents were clustered close to the theme location). More prominent peaks are characteristic of the high discrimination values, as for example peak 42 representing "nuclear weapons" and peak 44 representing "health physics".

FIG. 5 represents a database with the same number of documents and themes as in FIG. 4, however the themes have relatively large document sets and low theme discrimination values, as at peak 52 representing "lasers" and peak 54 representing "genetics".

Therefore, the ThemeScape function of the present invention can be summarized as follows:

(i) receive n-dimensional context vector from text engine for each document and cluster documents in n-dimensional space;

(ii) for each such cluster, receive from text engine associated gisting terms or topics;

(iii) creating a list of topics for each cluster;

(iv) creating global keyword list by combining the topics for each cluster and eliminating common terms (such as a, and, but, the);

(v) performing keyword query on topic, producing a list of documents associated with the topic;

(vi) identifying coordinates for all documents associated with the topic, producing a matrix of retrieved documents in the x,y display coordinates;

(vii) applying a smoothing function to each x,y pair, producing a z coordinate associated with the topic for each x,y pair; and

(viii) repeating steps (v) and (vi) for each term in the list identified in step (iv).

An embodiment of the present invention is shown in FIG. 6. The embodiment provides a method of determining and displaying the relative content and context of a number of related documents in a large document set. The relationships of a plurality of documents are presented in a three-dimensional landscape with the relative size and height of a peak in the three-dimensional landscape representing the relative significance of the relationship of a topic, or term, and the individual document in the document set. The steps of the process are shown in steps **602** through **614** of FIG. 6, including: (a) constructing an electronic database of a plurality of documents to be analyzed (step **602**); (b) creating a plurality of high dimensional vectors, one for each of the plurality of documents, such that each of the high dimensional vectors represents the relative relationship of the individual documents to the term, or topic attribute (step **604**); (c) arranging the high dimensional vectors into clusters, with each of the clusters representing a plurality of documents grouped by relative significance of their relationship to a topic attribute (step **606**); (d) calculating centroid coordinates as the center of mass of each cluster, the centroid coordinates being stored or projected in a two-dimensional plane (step **608**); (e) constructing a vector for each document, with each vector containing the distance from the document to each centroid coordinate in high-dimensional space (step **610**); (f) creating a plurality of term (or topic) layers, each of the term layers corresponding to a descriptive term (or topic) applied to each cluster, and identifying x,y coordinates for each document associated with each term layer (step **612**); and (g) creating a z coordinate associated with each term layer for each x,y coordinate by applying a smoothing function to the x,y coordinates for each document, and superposing upon one another all of the terms layers (step **614**).

It will be apparent to those skilled in the art that various modifications can be made to the methods disclosed herein for producing a three-dimensional representation of a database, without departing from the scope or spirit of the invention, and it is intended that the present invention cover modifications and variations of the methods claimed herein to the extend they come within the scope of the appended claims and their equivalents.

We claim:

1. A method of determining and displaying the relative content and context of a number of documents in a large document set, wherein the relationships of a plurality of documents are presented in a three-dimensional landscape with the relative size and height of a peak in the three-dimensional landscape representing the relative significance of the relationship of a topic attribute and the individual documents in the document set, comprising the steps of:

(a) building an electronic database of a plurality of documents;

(b) creating a plurality of high dimensional vectors, one for each of said plurality of documents such that each of said high dimensional vectors represents the relative relationship of the individual documents to the topic attribute;

(c) arranging said high dimensional vectors into clusters, each of said clusters representing a plurality of documents grouped by the relative significance of their relationship to a topic attribute;

(d) calculating centroid coordinates as the center of mass of each cluster, the centroid coordinates being stored or projected in a two-dimensional plane;

(e) constructing a vector for each document, said vector containing the distance from the document to each centroid coordinate in high-dimensional space;

(f) creating a plurality of term layers, each of said term layers corresponding to a descriptive term applied to each cluster, and identifying x,y coordinates for each document associated with each term layer; and

(g) creating a z coordinate associated with each term layer for each x,y coordinate by applying a smoothing function to the x,y coordinates for each document, and superimposing upon one another all of said term layers.

* * * * *

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Ruocco et al.

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[45] Date of Patent: Jan. 26, 1999

[54] PARALLEL DOCUMENT CLUSTERING PROCESS

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[73] Assignee: The United States of America as represented by the Secretary of the Army, Washington, D.C.

[21] Appl. No.: 606,951

[22] Filed: Feb. 26, 1996

[51] Int. Cl.[6] G06F 17/30

[52] U.S. Cl. 707/10; 707/5; 707/6

[58] Field of Search 395/611, 602, 395/605; 707/100, 2, 5, 10

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Assistant Examiner—Greta L. Robinson
Attorney, Agent, or Firm—Werten F. W. Bellamy

[57] ABSTRACT

A computer information processing system utilizes parallel processors for organizing and clustering a large number of documents into a large number of clusters for information analysis and retrieval. After the documents are translated into electronic digital documents, each document is converted into a vector based on weighted list of the occurence of different words and terms that appear in the document. The document vectors are grouped together into cluster vectors on different parallel processors according to similarities. New document vectors are simultaneously compared with existing cluster vectors in the different parallel processors.

1 Claim, 9 Drawing Sheets

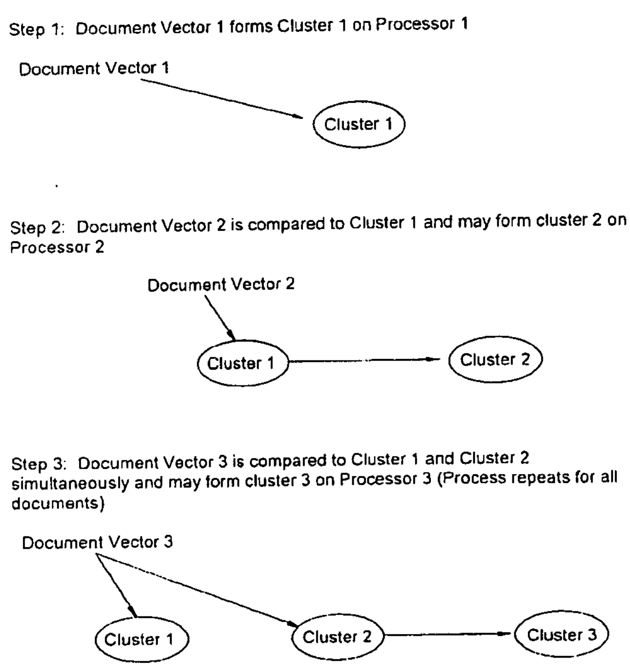


FIG. 1a
PRIOR ART

Document is "data base management system"

Form term signatures:	data	0000 0010 0000 1000
	base	0100 0010 0000 0000
	management	0000 0100 0001 0000
	system	0000 0000 0101 0000

FIG. 1b
PRIOR ART

Form document signature by Oring each column 0100 0110 0101 0000

FIG. 2a
PRIOR ART

Keyword-Boolean matrix for keywords APPLE, ORANGE, BANANA, GRAPE

Terms	D0	D1	D2	D3	D4	D5	D6	D7	D8	D9
APPLE	1	0	1	0	1	0	1	0	0	0
BANANA	0	0	0	1	0	1	0	1	0	0
GRAPE	0	0	1	0	0	0	1	0	1	1
ORANGE	0	1	1	1	1	1	0	0	0	0

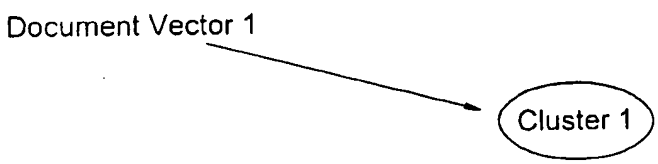
FIG. 2b
PRIOR ART

Inverted index for same terms:

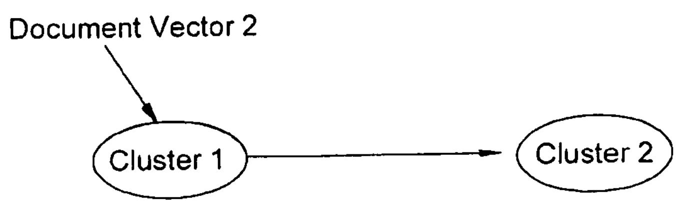
Terms	Documents
APPLE	D0, D2, D4, D6
BANANA	D3, D5, D7
GRAPE	D2, D6, D8, D9
ORANGE	D1, D2, D3, D4, D5

FIG. 3

Step 1: Document Vector 1 forms Cluster 1 on Processor 1



Step 2: Document Vector 2 is compared to Cluster 1 and may form cluster 2 on Processor 2



Step 3: Document Vector 3 is compared to Cluster 1 and Cluster 2 simultaneously and may form cluster 3 on Processor 3 (Process repeats for all documents)

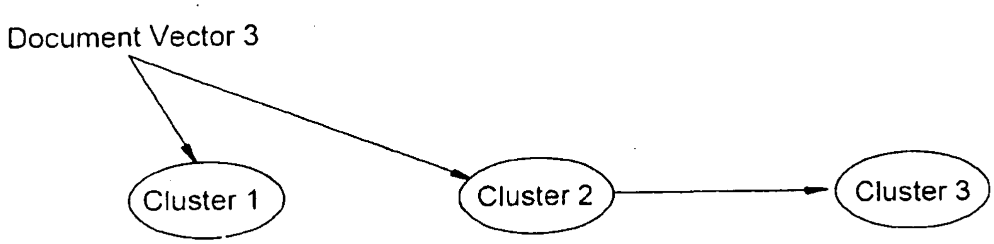


FIG. 4

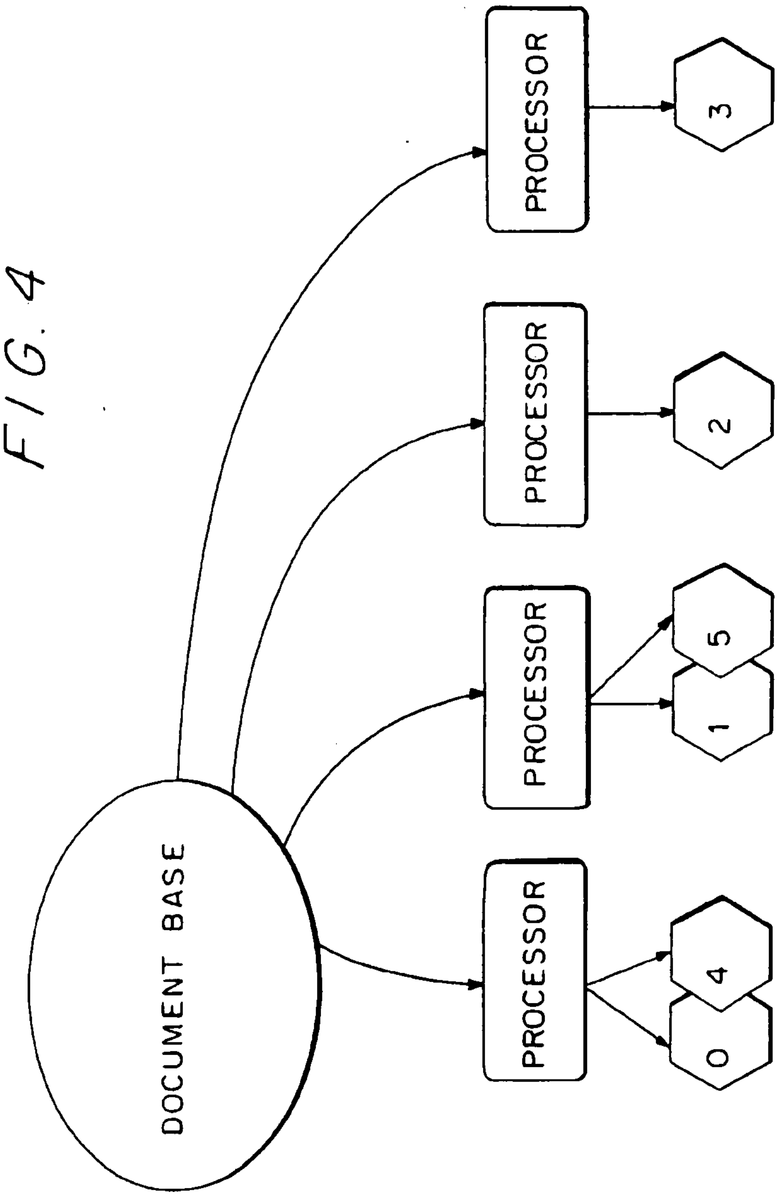

DOCUMENT BASE
PROCESSOR
PROCESSOR
PROCESSOR
PROCESSOR
0
4
1
5
2
3

FIG. 5

TIMES TO PERFORM CLUSTERING FOR [D,TA,C,1]

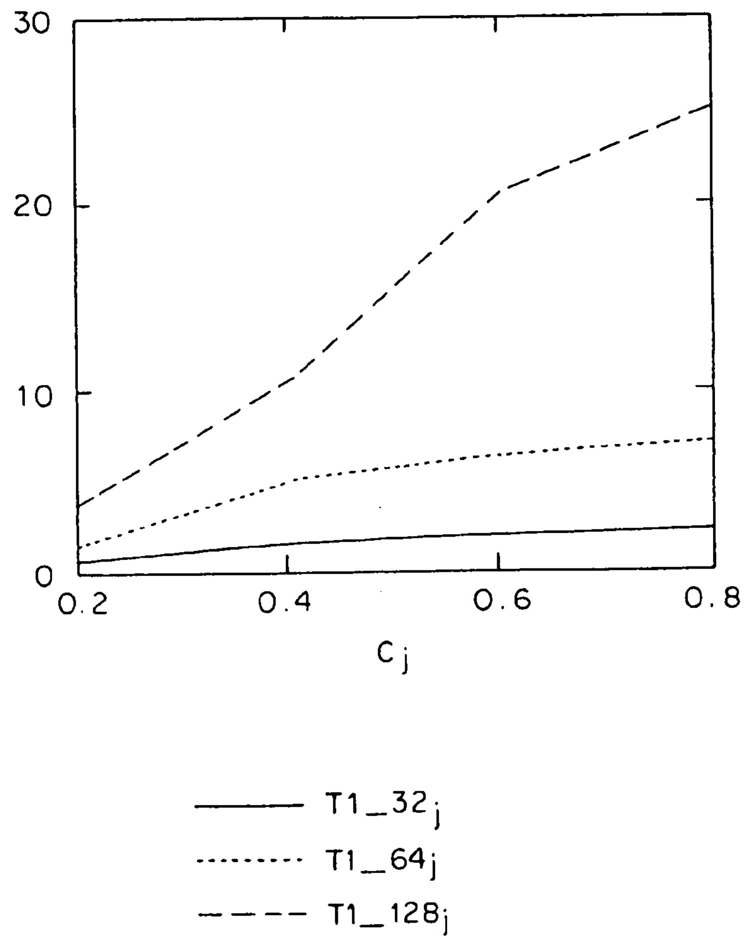


FIG. 6A

TIMES TO FORM CLUSTERS AND SPEEDUP FOR [D, TA, C, 2]

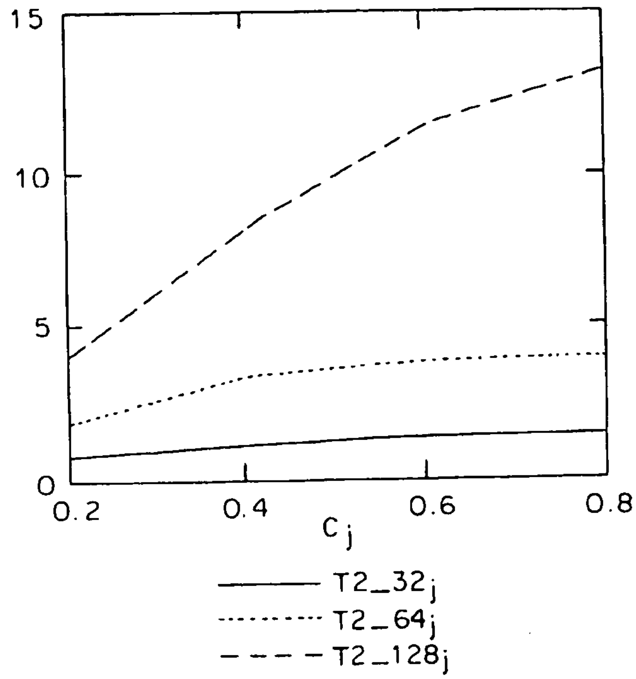


FIG. 6B

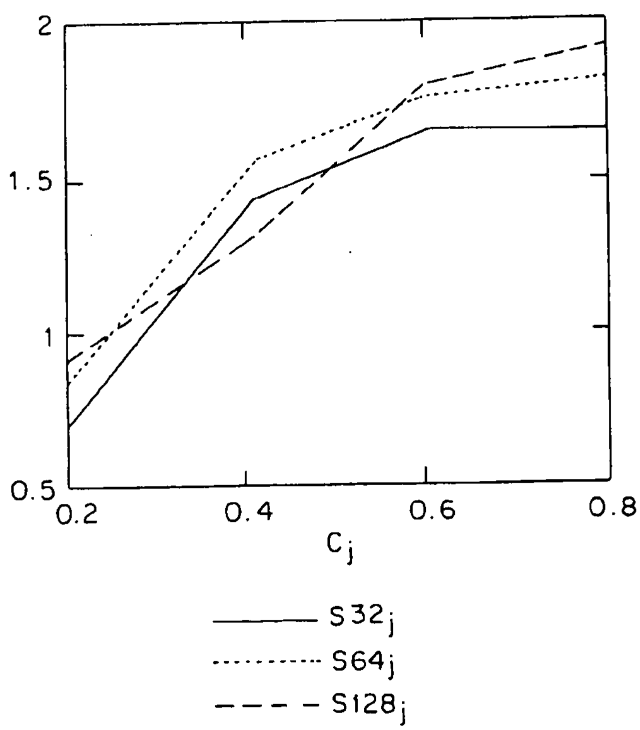


FIG. 7A

TIMES TO FORM CLUSTERS AND SPEEDUP FOR [D, TA, C, 4]

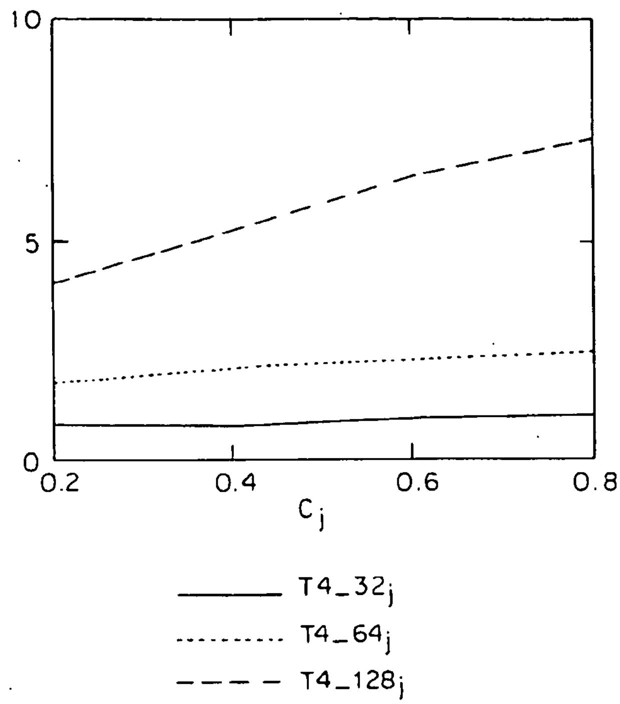


FIG. 7B

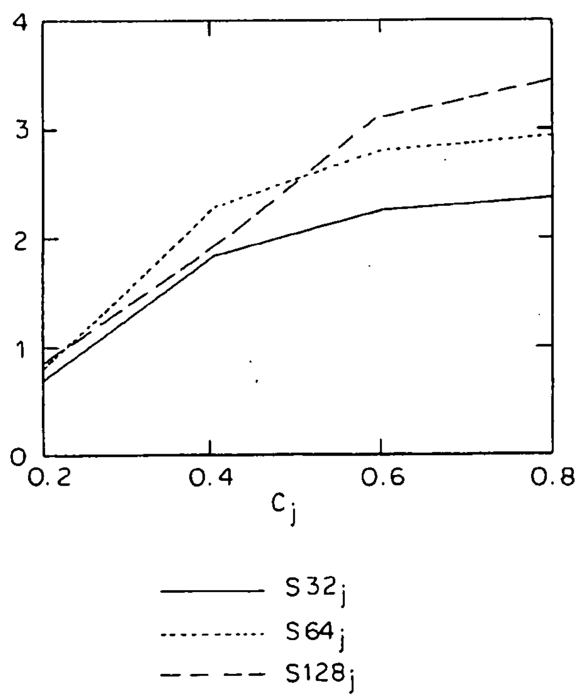


FIG. 8A

TIMES TO FORM CLUSTERS AND SPEEDUP FOR [D, TA, C, 16]

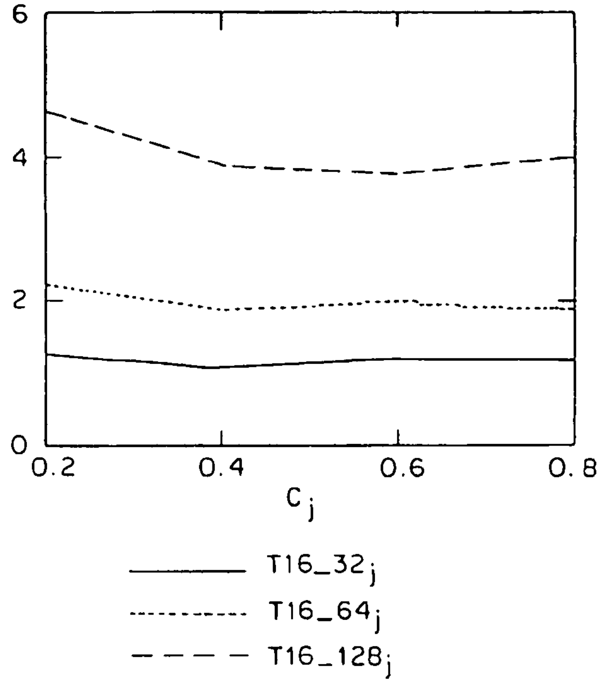


FIG. 8B

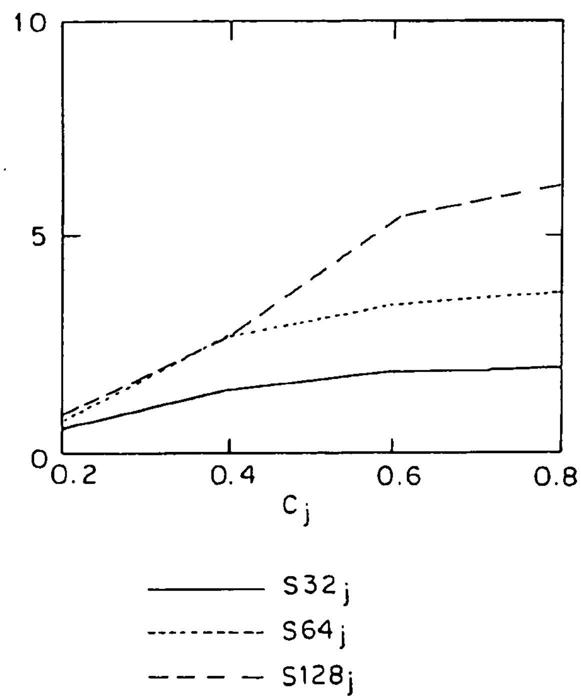


FIG. 9A

TIMES TO FORM CLUSTERS AND SPEEDUP FOR [D, TA, 0.8, L]

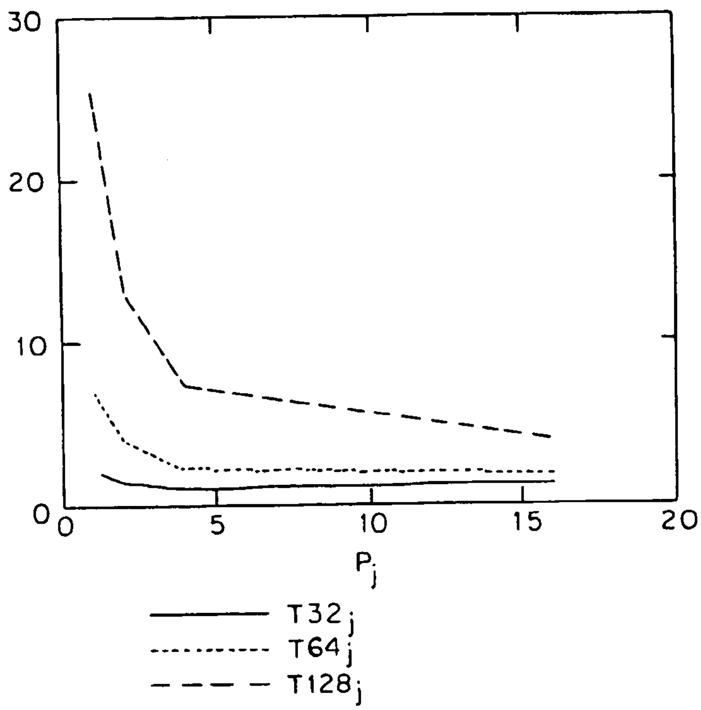
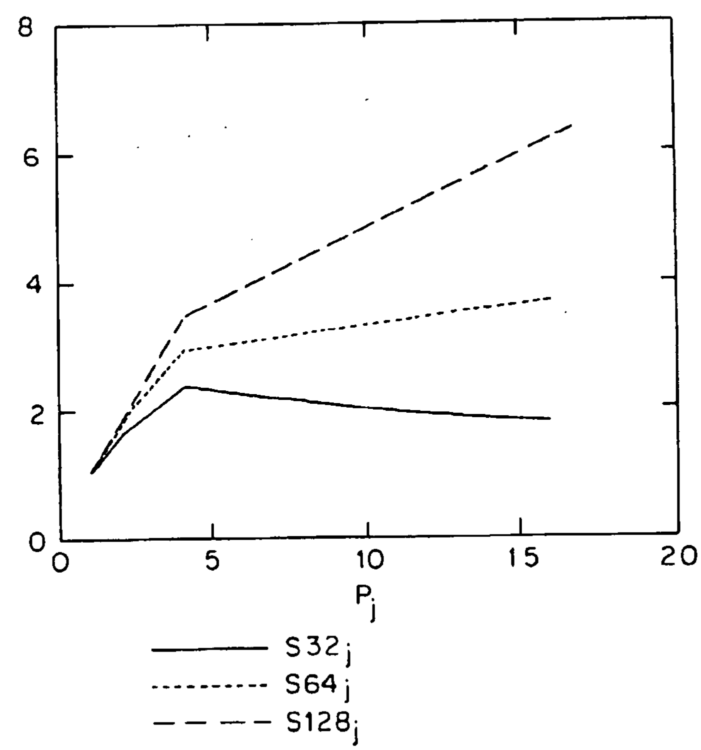


FIG. 9B



PARALLEL DOCUMENT CLUSTERING PROCESS

FIELD OF INVENTION

The present invention relates to a clustering process to organize a vast amount of text-based documents into related groups of generally accepted clusters for subsequent query-driven retrieval and information analysis.

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DESCRIPTION OF DIAGRAMS

A complete appreciation of the invention and its advantages can be attained by reference to the background leading to the invention and the summary and detailed description of the invention when considered in conjunction with the accompanying drawings:

FIG. 1 shows the formation of a signature file.

FIG. 2 shows the formation of a keyword-Boolean matrix and inverted index.

FIG. 3 provides a general overview of the invention's operation

FIG. 4 provides a generalized result of the invention.

FIG. 5 shows time to form clusters on 1 processor.

FIG. 6 shows time to form clusters and speedup for 2 processors.

FIG. 7 shows time to form clusters and speedup for 4 processors.

FIG. 8 shows time to form clusters and speedup for 16 processors.

FIG. 9 shows times to form clusters and speedup across processors.

Table 1 is the number of clusters for each permutation of the Wall Street Journal Set.

Table 2 is the time to make the clusters with 1 processor.

Table 3 is the time to make the clusters with 2 processors.

Table 4 is the time to make the clusters with 4 processors.

Table 5 is the time to make the clusters with 16 processors.

Table 6 represents the speedup of 2 processors over 1 processor.

Table 7 represents the speedup of 4 processors over 1 processor.

Table 8 represents the speedup of 16 processors over 1 processor.

Table 9 represents the efficiency of using 2 processors.

Table 10 represents the efficiency of using 4 processors.

Table 11 represents the efficiency of using 16 processors.

BACKGROUND OF INVENTION

Information retrieval is the process of retrieving documents which are relevant to a query generated by a user. There are four dominate models for information retrieval: full-text scanning, keyword-Boolean operations, signature files, and vector-space. The models can be characterized as either formatted or unformatted. An unformatted model takes each document exactly as it appears in the document set. In other words, the document does not undergo any processing into a different form. Formatted models process the documents into a separate form or data structure. Query processing is done with separate forms or data structures.

One model is full-text scanning. This model takes a phrase from the user and searches each document in a collection for an exact match. This model is unformatted, hence each document must be completely scanned with each query. There are some efficient algorithms for text scanning. However this model, in general, is only used in small document sets where the user is familiar with the documents, i.e., personal files.

Formatted models take a document and convert them to some other form. Usually, this form is based on an ability to discriminate among documents. One way to discriminate is to identify words within the documents and build the formatted structure from discriminating words. These words are frequently referred to as descriptors. In many cases, descriptors are reduced to word stems. In other words, terms like "engineer", "engineering", or "engineered" would all reduce to the stem "engineer".

A signature file is formed from the signatures of a document set. To form a signature, each term in a document is converted to a standard size term consisting of 0's and 1's. Once each term is converted, the document signature is formed by performing an ORing operation. FIG. 1 details the formation of a document signature. To perform a query, the query is converted to a query signature. This signature is compared to each document signature. A match occurs if a "1" in the query signature can be aligned with a "1" in a document query. Unfortunately, if there is a match it is unknown if the match occurs because the document matches the query or simply because the process of conversions attributed to the alignment. A document which is retrieved due to alignment based on the conversion process yet does not match the actual query is called a "false hit". Signature files tend to be used as a filtering process which retrieves potential matches with some other process use to screen false hits from the retrieved set.

Keyword-Boolean models typically are represented by a matrix where the columns represent documents and the rows represent keywords. If a keyword appears in a document then the row corresponding to the term and the column corresponding to the document has a "1" placed in it. FIG. 2*a* shows a typical Boolean model matrix. A query is formulated using the Boolean operators AND, OR, NOT. Each term in the query is compared to the matrix. If a "1" appears in the [row, column] corresponding to the [term, document] that document is placed into a set of potential documents. Once documents are placed in the set the Boolean operations are performed. In effect the set of potential documents is pared down to the final set presented to the user. However, for each query, each term must be tested for in each document. Searching can be made more efficient by the use of an inverted index, An inverted index for information retrieval is much the same as the index of a textbook. It identifies keywords and indicates which documents contain those keywords. FIG. 2*b* shows a scheme for an inverted index. While improving searching time, the indices themselves can be very large. Keyword-Boolean systems are dependent on the indexing scheme. If a term is not a keyword, there is no way to query for that term within documents. If a new word is added to the index, each document may need to be re-examined to identify if the document contains the new term. Assigning the keywords as descriptors of documents is a complex problem [TIBE93]. It has been shown that the probability of two people using the same descriptors to categorize a document is low (10–20%) [CHEN92].

The last model to be discussed is the vector-space model. In this model, each document is considered to be a collection of terms. The number of times each word occurs is considered that term's weight. The terms and weights for each document can be organized into a document vector consisting of n-dimensions, where n is the number of terms. A query is also a collection of terms. A query can be converted into a query-vector and the query vector is compared to the document vector. Document and query vectors are compared using vector operations and if some threshold of similarity is reached, the document is considered for retrieval. Typical measures of similarity are the Cosine, Dice, or Jacquard similarity measures.

The formatted models (signature files, keyword-Boolean Operations, Vector-Space) process the documents to form different data structures. These data structures ignore the relationships between the words in a document. If word concordance is a concern, some additional data structure must be maintained. Word count, or the number of times a given word occurs in a document, is lost in signature files, and in Boolean models. Word count can be considered as inherent in the value of attributes in the vector-space model.

All the models have been described in terms of how documents compare to a query. However, none of the models describe how documents relate to each other. The signature file model, the text scanning model, and the Boolean models simply do not have capabilities to relate documents to each other. The Vector-space model, with its ability to measure similarity is readily capable of determining how documents compare to each other. This ability forms the underlying premise of the idea of clustering.

The basic idea of clustering is that items which are similar can be grouped together. Each group, or cluster, has a centroid vector, which is the average of the document vectors making up the cluster. Query vectors are compared to the cluster centroids, if a match is determined, the entire cluster is retrieved. Clusters can reduce the search requirement as each centroid contains information about numerous documents.

Clustering has been used in retrieval systems. However, it has always been done in a sequential fashion. As new documents are added to a collection they are not immediately available to the user. Instead they are held until such time as a sufficient number of new documents have been acquired. Then, in an off line process, the new documents and old documents go through the clustering process. This results in a new set of cluster centroids. The new set of cluster centroids is eventually provided to the user as a new release or version. As document sets increase, the amount of time between versions increases as well. However, if a document set doubles, it takes four times as long to form the new clusters. This can result in an unacceptable time delay from the time a new document is acquired to the time a user actually has access to that document. The Parallel Document Clustering Process can greatly reduce this time.

SUMMARY OF INVENTION

It is the object of this invention to provide an efficient method of organizing a large body of documents into clusters for subsequent retrieval.

It is a further object of the invention to provide a fast method of clustering to reduce the amount of time a document waits from its receipt into the document set until it is available for retrieval by users.

A more specific object of the invention is to perform the process on any available multiple processor (parallel) machine.

The invention is a process for forming clusters of large document sets using multiple processor machines. The process is useful for identifying similarity amongst documents and for subsequent use in document retrieval systems. For demonstration purposes, the Single-Pass Heuristic is used as the clustering method. This method is generally accepted within the information retrieval community.

Text documents are converted to document vectors. Clusters of documents are represented by cluster vectors which have the same format as document vectors. A cluster vector is made by taking the numerical average of all the documents which comprise the cluster. A document vector is compared to each cluster vector. As soon as a determination is made that the document is similar to a cluster, the comparisons stop and the document is added to that cluster. In the event a document is not similar to any cluster, a new cluster is formed.

The invention follows the same tenets of forming a document vector which is compared to cluster vectors. However, the key innovation is that instead of comparing a document vector to a single cluster, it compares the document vector simultaneously with P clusters, where P is the number of processors within the system. Each processor is responsible for creating and maintaining certain clusters. Each processor uses the same document vector. The processor compares this document vector to each of its clusters. When a sufficient threshold of similarity is exceeded, the processor records which cluster vector is similar to the document vector. When all processors have compared the document vector, a decision is reached to determine to which cluster the document vector is added to. If a determination is made that the document was not similar to any existing cluster, a processor is designated to create a new cluster.

By way of example, the process begins by converting the first document vector into a cluster vector. This vector is stored in processor **1**. The next document is compared to this vector. Assuming the threshold is not exceeded, the process forms cluster **2** on processor **2**. The third document is now compared simultaneously with cluster **1** and **2**. If the document cannot be added to either cluster, then cluster **3** is formed on processor 3. The next document is now compared simultaneously with cluster 1, cluster 2 and cluster 3. This process continues until all documents in the set are placed into appropriate clusters. FIG. 3 shows this process. While there is no theoretic limit to the number of processors, a claim of the invention is that it performs on realistic, existing machines. Therefore, each processor may be responsible for more than one cluster. FIG. 4 shows the overall effect of the process on a machine with 4 processors.

DETAILED PROCESS

Each text document is scanned to create a document vector, Stop words are removed and the number of times each word appears in a document is counted. Each unique word in a document is given an administrative number based on a master dictionary. The document vector is basically a set of paired numbers. The first pair indicates the total number of words in the document and the second number of the pair represents the number of unique words within the document. Each subsequent pair is made of up the number of appearances of a word and the administrative number of that word. Formation of the document vector is done off line and is not part of the invention. Each cluster has a uniquely designated global number. The cluster centroid vector has the same form as a document vector. That is a series of paired numbers. The first pair represents the total number of words in the cluster and the total number of unique words in the cluster. Each subsequent pair is made of up the number of appearances of a word and the administrative number of that word. The cluster vector is formed as the mathematical average of the document vectors within the cluster. The following formula shows how each element of a document vector is added to its corresponding element in a cluster vector:

$$\frac{c_{j,i} + y_i}{C_{j,N}} \qquad (1)$$

$c_{j,i}$ = Weight of appearances of word i within cluster C_j

y_i = Weight of appearances word i within document Y

N = Number of documents within cluster C_j

Weight based on appearances of term i/

total words of cluster or document

Clusters are formed based on a similarity measure between the cluster centroid and a document vector. One popular similarity measure is the COSINE measure based on the formula:

$$\mathrm{COSINE}(C_j, Y) = \frac{\Sigma\, c_{j,i} y_i}{\sqrt{\Sigma\, c_{j,i}^2\, \Sigma\, y_i^2}} \qquad (2)$$

$c_{j,i}$ = weight of ith term of cluster C_j

y_i = weight of ith term of document Y

If COSINE(C_j,Y) exceeds a threshold (ranging from 0 to 1), the document and cluster are considered to be similar. The document is added to the cluster using equation 1. Every cluster C is compared to document Y until either the threshold is exceeded or all clusters have been checked. In the latter case, a new cluster is formed. Forming a new cluster is very simple. The document vector is simply redesignated as a cluster and given a number. To put the threshold into perspective, a threshold of 0 implies that any document will match a cluster. A threshold of 1 implies that only documents which have exactly the same words and exactly the same number of appearances of those words will be considered similar.

Each processor accesses the same document vector at the same time. Using equation (2), a processor determines if a document is similar to any of its clusters. It is possible for a document vector to be similar to more than one cluster. However, the tenets of the Single-Pass method are such that a document is only placed into the first cluster which exceeds the threshold. For the invention to produce the same results as the Single-Pass, there must be communications among the processors to determine which cluster was the first to have the threshold exceeded. It is important to note that the use of the term "first cluster" is based on the order the clusters were formed. Cluster 1 is formed before cluster 2, which is formed before cluster 3, etc. Since the clusters are numbered globally, the cluster with the lowest global number is determined to be the cluster which incorporates the document. So if processor 2 reports the threshold was exceeded with cluster 7 and processor 5 reports that the threshold was exceeded on cluster 5 then the document is added to cluster 5. This assignment occurs even if the actual computations by processor 2 where finished ahead of processor 5. If no cluster is found, the system generates a new cluster and one of the processors takes responsibility for the cluster. Clusters are apportioned to processors in a modulus fashion, that is:

$$P_{cluster\ i} = i \bmod P_t \qquad (3)$$

Where:

$P_{cluster\ i}$ is the Processor designated for cluster i

i is the cluster being formed

P_T is the total number of processors within the system

The invention was used with a set of articles from the Wall Street Journal. The articles were written at different times of the year, by different reporters, and cover an assortment of topics. They are also of varying lengths. In other words, the document set is not categorized into any preestablished category, such as, computer oriented, financially oriented, legally oriented, etc. The documents were formed into individual document vectors and each is stored as a separate file with a unique file name. There is a master file which contains the file names of the document vectors. When the vectors were formed stop words were removed but there was no stemming. Stemming can be easily incorporated into the scheme if desired as all conversion from text format to vector format is outside the scope of the invention.

There are several parameters which must be established prior to executing the process. These are:

a) D, the number of documents in the document set.

b) O, the order in which document vectors are accessed for comparison.

c) C, the threshold value of the COSINE coefficient.

d) P, the number of processors in the actual system.

The Single-Pass method places a document into the first cluster which exceeds the threshold. This has two very characteristic results. The first characteristic is that the clusters which are formed first tend to be larger (contain more documents) than clusters which are formed later in the process. The second characteristic is that the process is order-dependent. That means if the order in which the document vectors are compared changes, the clusters may change as well. These two characteristics are known and generally accepted as a by-product of the Single-Pass method. To show the generality of the invention, results are based on five different orderings of the document set. The ordering of the document vectors is done through manipulation of the master file of document vectors.

The first runs were done with a random ordering (R) of the documents. Basically, this can be considered as taldng the documents in the order in which they arrived to the system. While the document vectors are formed, little is known about their content. However, once a document vector is formed, it is very easy to identify two characteristics. The first characteristic is the total number of words in the vector and the second characteristic is the number of unique words in the document vector. These values are provided by the first numbered pair of the document vector. With this information, it is possible to arrange the document vectors based on total words or number of unique words. This being the case, the document vectors were ordered by total words in ascending order (TA) and descending order (TD). Ordering was also done based on number of unique words in ascending order and descending order, UA, and UD, respectively.

The threshold coefficient is the basis of comparison between a document and a cluster. If the cosine exceeds this threshold, the document and cluster are deemed to be similar. The coefficient can range from 0.0 to 1.0. The higher the value, the more similar a document must be in order to be added to a cluster. While the range can be 0.0 to 1.0, values at the extremes have little meaning. A value of 0.0 implies that there will be a single cluster incorporating all the documents. A value of 1.0 would basically filter all the documents and only cluster those which are duplicates. The invention was run on coefficients of 0.2, 0.4, 0.6, and 0.8.

The intent of the invention is to be used with large document sets. To show the effect of the invention as document set size increases, document sets of 32, 64 and 128 were used. These sets were run at each of the four coefficients and in each of the five different orders.

The last parameter to be established is the number of processors to use. While there is no theoretic limit to the number of processors, the intent of the invention is to show the effectiveness on a real, practical, and commercially available machine. The process was run initially on 1 processor. This indicates the time the process would take on a regular, sequential machine. The process was run on machines consisting of 1, 2, 4, and 16 processors. A run then consists of a combination of the four parameters [D, O, C, P]. In total, there were 240 permutations run, each permutation was run 5 times. Results are based on the average of these runs.

The initial runs were used to establish the number of clusters. In general, the fewer the clusters, the broader the scope of those clusters. The more clusters there are, the more specific the scope of the clusters. Correspondingly, there tend to be more clusters at higher values of the coefficient. There is no direct link between selecting a coefficient and the desire to form a specific number of clusters. Table 1 provides the results of the clustering process itself. It is evident that the value of the coefficient is the major determining factor in the number of clusters formed. In the Single-Pass method, the number of processors used has no effect on the number or composition of the clusters formed. In other words, the 6 clusters formed with the 32 document set, in random order with a coefficient of 0.2 are the same whether the process was run on 1 processor or 16 processors. It is interesting to note that the ordering scheme TA and UA tend to provide the most clusters while the schemes TD and UD provide the least. It should be made clear that it has yet to be determined if there is a combination of [D, O, C] which results in an optimal clustering of any document set.

Tables 2, 3, 4, and 5, represent the time it takes to do the process on 1, 2, 4, and 16 processors. Table 2 is the process time on one processor. As such, it reflects the process time on the typical sequential machine. This is the basis for comparison as more processors are added to a system. The time it takes to perform the process on multiple processors has two main components. The first component is the time it takes to do actual processing, e.g. mathematical operations. The second component is the time it takes to do internal message passing. The times depicted in tables 3, 4, and 5 are the combined total of the two components for each [D, O, C, P] combination. The effects of the components will be explained in accompanying narrative. There are three factors which are used in evaluating the process. The first is simply the time to perform the algorithm. The second factor is speedup which indicates how much faster an algorithm runs as more processors are added. It is a value ranging from 1 to P, the number of processors. The third factor is efficiency, or how much effort is each processor contributing to the accomplishment of a task. Efficiency is a value of 0 to 1. In general, the higher the speedup and efficiency the better an algorithm performs. It is also generally accepted that the best speedup which can be attained is when speedup is the same as the number of processors and the best that efficiency can be is 1. Speedup and efficiency can be mathematically defined by:

$$\text{(a) } S_P = \frac{T_1}{T_P} \quad \text{(b) } \eta_P = \frac{S_P}{P} \tag{4}$$

S_P = Speedup with P processors

T_1 = Time with 1 processor

T_P = Time with P processors

η_P = Efficiency with P processors

Table 2 indicates the time, in seconds, it takes to form the clusters for each configuration using 1 processor. This becomes the basis for comparison of the process as more processors are added. Each time represents a combination of the four parameters [D, O, C, P] so conclusions are described in terms of isolating parameters. As D, O, and P are held constant, it is clear that increasing C causes an increase in execution time. For example [32,R,0.2,1] takes 0.937 seconds whereas [32,R,0.4,1] takes 1.354 seconds, [32,R,0.6,1] takes 2.361 seconds and [32,R,0.8,1] takes 2.495 seconds. In general, it can be seen that the time increases as C increases. In other words, it takes longer to make more clusters which is intuitive. It is also intuitive that it takes one processor longer to perform the algorithm as the number of documents increase. This is evident in holding O, C, P constant and allowing D to change from 32 to 64 and then to 128.

Table 3 is the time to perform the algorithm for each permutation with two processors or [D, O, C, 2]. It can be seen that for permutations where C=0.2, the algorithm does worse than with 1 processor. This is to be expected given the nature of the Single-Pass method. As previously stated, the Single-Pass tends to put documents into the first clusters. So the first processor is initially doing work while the second processor is idle. This accounts for poor speedup and efficiency as well. In effect, only one of the processors is working. Note, however, that as the value of C increases, so does the number of clusters. As these clusters are apportioned, there is more work to do and each processor takes on a more even distribution of the load. This is especially seen as both D and C increase.

Table 4 shows the times to perform clustering with four processors, and Table 5 represents the results of using 16 processors. Tables 6 through 8 reflect the speedup for P=2, 4, and 16, respectively. By definition, there is no speedup when only one processor is used. The values in these tables were derived from equation (4)(*a*). Equation (4)(*b*) was used to determine the efficiency of the invention as the number of processors increases. The results are available for 2, 4, and 16 processors in Tables 9 through 11. A graphic representation of the results is presented in FIGS. 5 through 9. For clarity, the results of O=TA has been isolated.

To show the effects of the invention over a range of document set sizes, various graphs are superimposed over the same set of axis. To allow for superimposing the graphs, a special notation has been adopted. "T" represents time, the digit represents the number of processors and the number following the underscore represents the size of the document set. So T1_32 represents the time needed for 1 processor operating on 32 documents. In a similar fashion, T16_128 represents the time for 16 processors operating on 128 documents. The use of "C" along the bottom axis represents the value of the coefficient (0.2 through 0.8). The subscripted letter, j, serves as a counter to ensure the alignment of results of the documents sets with the appropriate value of the coefficient. "S" is used to represent speedup. S32 represents speedup for 32 documents, S64 is speedup for 64 documents etc. Again, the subscripted letter, j, ensures proper alignment of speedup based on the document sets and the coefficient. In the final figure, the "P" represents the number of processors used with "j" aligning results for each value of "P".

FIG. 5 shows the time to cluster the document sets for each value of C and D. As intuition would indicate, it longer to cluster a larger number of documents into a larger number of clusters. The significance of FIG. 5 is in how it compares to the performance as the number of processors increases. The subsequent figures represent time with various values of P. The speedup chart which accompanies each time chart reflects the performance of a given value of P compared P=1.

FIG. 6 displays the results of using 2 processors. The chart shows a decrease in time using the 2 processors versus using 1 processor. The speedup chart reflects how much faster the invention is performing. To determine the speedup select the coefficient of interest, for example 0.6. Draw a line straight up until that line intersects with the lines representing the document set of interest, for example, S128. From the intersection point draw a line straight to the left. The point where this line intersects the vertical axis is the speedup. With the values of C=0.6, and D=128 (S128) the speedup is 1.79. In other words, [128, TA,0.6,2] is 1.79 times faster than [128,TA,0.6,1].

The next figures represent results for P=4 and P=16. In all cases it can be seen that the speedup is better as D and C increase. It is clear from FIG. 8 that there is a marked increase in the performance of the invention as D, C, and P have increased.

FIG. 9 isolates O=TA and C=0.8 to better show time to perform the clustering and the invention's speedup across an increase in P. FIG. 9 shows several things. First it is clear that speedup will decrease if D is constant and P is allowed to increase. Clearly, the invention takes less time as the number of processors increase. However, note that the curve for D=128 continues to decrease. It is important to note that speedup is increasing as both D and P increase. For example, the D=32 has a break point at P=4. This break point indicates it takes longer to perform the clustering as the number of processors increases. This increase is caused because the document set is not large enough to keep each processor productively employed. Also, as the number of processors increases, so to does the amount of time spent passing messages. The breakpoint is an indicator of when the messaging overhead takes longer than the processing time to perform the clustering. The break point is not yet reached for D=64 but is flattening out. The figure clearly shows that D=128 is still rising at P=16 which indicates P can increase and still provide reasonable speedup performance. More importantly, the figure shows two significant trends. The first is that performance is better if D increases while P is held constant. The other trend is the increased performance of the algorithm for increases in D and P. These results clearly show the invention does as stated: that is efficient clustering of large document sets in a practical parallel environment.

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
32	R	6	19	30	32
	TA	9	20	30	32
	TD	5	17	30	32
	UA	9	19	30	32
	UD	5	17	30	32
64	R	6	34	53	56
	TA	10	38	53	58
	TD	4	32	53	58
	UA	10	37	53	58
	UD	4	34	53	58
128	R	8	52	97	120
	TA	11	60	101	122
	TD	6	49	94	122
	UA	11	57	100	122
	UD	6	53	96	122

Table 1 represents number of clusters based on number of documents, order of documents and coefficient of similarity.

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
32	R	0.937	1.354	2.361	2.495
	TA	0.560	1.530	2.138	2.241
	TD	1.270	1.770	2.719	2.795
	UA	0.551	1.535	2.124	2.239
	UD	1.280	1.761	2.712	2.789
64	R	2.651	5.488	8.377	8.680
	TA	1.432	5.019	6.470	7.058
	TD	3.429	6.287	9.131	9.456
	UA	1.592	4.898	6.393	7.019
	UD	3.438	6.330	9.114	9.458
128	R	7.278	17.913	27.252	29.419
	TA	3.591	10.354	20.219	24.969
	TD	8.881	16.749	27.561	32.071
	UA	3.538	9.686	19.435	24.937
	UD	8.938	15.521	28.184	32.152

Table 2 represents the time required to form clusters using D = 1. Time includes the processing time and the messaging time.

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
32	R	1.115	1.273	1.541	1.525
	TA	0.815	1.087	1.310	1.362
	TD	1.577	1.317	1.671	1.693
	UA	0.766	1.064	1.363	1.357
	UD	1.477	1.372	1.690	1.690
64	R	3.028	4.131	4.657	5.148
	TA	1.729	3.259	3.717	3.886
	TD	3.860	4.492	5.168	5.266
	UA	1.719	3.230	3.731	3.958
	UD	3.821	4.041	5.158	5.251

-continued

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
128	R	5.955	12.279	14.580	16.227
	TA	4.002	8.069	11.297	13.015
	TD	9.561	12.068	15.792	17.384
	UA	3.937	8.002	11.152	13.312
	UD	9.617	10.554	15.885	16.951

Table 3 represents the time required to form clusters using D = 2. Time includes the processing time and messaging time.

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
32	R	1.204	1.014	1.087	1.089
	TA	0.803	0.829	0.943	0.944
	TD	1.489	1.148	1.201	1.172
	UA	0.896	0.850	0.956	1.040
	UD	1.511	1.219	1.156	1.181
64	R	2.981	2.844	2.867	3.141
	TA	1.751	2.157	2.288	2.392
	TD	3.841	3.55	3.031	3.146
	UA	1.846	1.973	2.288	2.408
	UD	3.849	2.857	3.050	3.138
128	R	7.951	8.529	8.450	9.463
	TA	4.023	5.303	6.469	7.243
	TD	9.670	8.560	8.618	9.428
	UA	4.020	5.084	6.405	7.305
	UD	9.672	7.209	8.707	9.258

Table 4 represents the time required to form clusters using D = 4. Time includes the processing time and the messaging time.

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
32	R	1.474	1.252	1.216	1.237
	TA	1.292	1.071	1.170	1.192
	TD	1.740	1.371	1.303	1.257
	UA	1.315	1.252	1.158	1.231
	UD	1.776	1.400	1.247	1.219
64	R	3.250	2.071	2.145	2.138
	TA	2.209	1.911	1.922	1.903
	TD	3.919	2.557	2.376	2.144
	UA	2.253	1.952	1.957	1.916
	UD	3.950	2.450	2.178	2.069
128	R	8.076	4.500	4.410	4.549
	TA	4.624	3.884	3.760	4.004
	TD	9.649	4.802	4.435	4.683
	UA	4.491	3.987	3.812	3.945
	UD	9.587	4.740	4.510	4.491

Table 5 represents the time required to form clusters using D = 16. Time includes the processing time and the messaging time.

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
32	R	0.840	1.064	1.532	1.636
	TA	0.687	1.408	1.632	1.645
	TD	0.805	1.344	1.627	1.651
	UA	0.710	1.443	1.558	1.650
	UD	0.867	1.284	1.605	1.650
64	R	0.875	1.328	1.799	1.686
	TA	0.828	1.540	1.741	1.816
	TD	0.888	1.400	1.767	1.796
	UA	0.926	1.516	1.713	1.773
	UD	0.9	1.566	1.767	1.801
128	R	1.222	1.459	1.869	1.813
	TA	0.897	1.283	1.790	1.918
	TD	0.929	1.388	1.745	1.845
	UA	0.899	1.210	1.743	1.873
	UD	0.929	1.471	1.774	1.897

Table 6 represents the speedup attained using D = 2.

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
32	R	0.778	1.335	2.172	2.291
	TA	0.697	1.846	2.267	2.374
	TD	0.853	1.542	2.264	2.385
	UA	0.615	1.806	2.222	2.153
	UD	0.847	1.445	2.346	2.362
64	R	0.889	1.930	2.922	2.763
	TA	0.818	2.327	2.828	2.951
	TD	0.893	1.771	3.013	3.006
	UA	0.862	2.483	2.794	2.915
	UD	0.893	2.216	2.988	3.014
128	R	0.915	2.100	3.225	3.109
	TA	0.893	1.952	3.126	3.447
	TD	0.918	1.957	3.198	3.402
	UA	0.880	1.905	3.034	3.414
	UD	0.924	2.153	3.237	3.473

Table 7 represents the speedup attained using D = 4.

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
32	R	0.636	1.081	1.942	2.017
	TA	0.433	1.429	1.827	1.880
	TD	0.730	1.291	2.087	2.224
	UA	0.419	1.226	1.834	1.819
	UD	0.721	1.258	2.175	2.288
64	R	0.816	2.650	3.905	4.060
	TA	0.648	2.626	3.366	3.709
	TD	0.875	2.459	3.843	4.410
	UA	0.707	2.509	3.267	3.663
	UD	0.870	2.584	4.185	4.571
128	R	0.901	3.981	6.180	6.467
	TA	0.777	2.666	5.377	6.236
	TD	0.920	3.488	6.214	6.848
	UA	0.788	2.429	5.098	6.321
	UD	0.932	3.274	6.249	7.159

Table 8 represents the speedup attained using D = 16.

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
32	R	0.420	0.532	0.766	0.818
	TA	0.343	0.704	0.816	0.822
	TD	0.403	0.672	0.813	0.826
	UA	0.359	0.721	0.779	0.825
	UD	0.433	0.642	0.803	0.825
64	R	0.438	0.664	0.900	0.843
	TA	0.414	0.770	0.871	0.908
	TD	0.444	0.700	0.883	0.898
	UA	0.463	0.758	0.857	0.887
	UD	0.450	0.783	0.883	0.900

-continued

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
128	R	0.611	0.729	0.934	0.906
	TA	0.449	0.641	0.895	0.959
	TD	0.465	0.694	0.873	0.923
	UA	0.449	0.605	0.872	0.937
	UD	0.465	0.735	0.887	0.948

Table 9 represents the efficiency attained using D = 2.

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
32	R	0.194	0.334	0.543	0.573
	TA	0.174	0.461	0.567	0.594
	TD	0.213	0.386	0.566	0.596
	UA	0.154	0.451	0.555	0.538
	UD	0.212	0.361	0.586	0.590
64	R	0.222	0.482	0.730	0.691
	TA	0.205	0.582	0.707	0.738
	TD	0.223	0.443	0.753	0.752
	UA	0.215	0.621	0.698	0.729
	UD	0.223	0.554	0.747	0.753
128	R	0.229	0.525	0.806	0.777
	TA	0.223	0.488	0.781	0.862
	TD	0.229	0.489	0.799	0.850
	UA	0.220	0.476	0.758	0.854
	UD	0.231	0.538	0.809	0.868

Table 10 represents the efficiency attained using D = 4.

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
32	R	0.040	0.068	0.121	0.126
	TA	0.027	0.089	0.114	0.117
	TD	0.046	0.081	0.130	0.139
	UA	0.026	0.077	0.115	0.114
	UD	0.045	0.079	0.136	0.143
64	R	0.051	0.166	0.244	0.254
	TA	0.041	0.164	0.210	0.232
	TD	0.55	0.154	0.240	0.276
	UA	0.044	0.157	0.204	0.229
	UD	0.054	0.162	0.262	0.286

-continued

D	O	C			
Documents	Order	Coef = 0.2	Coef = 0.4	Coef = 0.6	Coef = 0.8
128	R	0.056	0.249	0.386	0.404
	TA	0.049	0.167	0.336	0.390
	TD	0.058	0.218	0.388	0.428
	UA	0.049	0.152	0.319	0.395
	UD	0.058	0.205	0.391	0.447

Table 11 represents the efficiency attained using D = 16.

We claim:

1. In an arrangement of parallel processors in a computer information processing system, a parallel clustering method for examining preselected documents and grouping similar documents in the parallel processors for subsequent retrieval in an electronic digital format from the computer information processing system, the steps comprising:

converting each preselected document into an electronic document in digital format;

converting each electronic document into a vector, whereby a vector is a weighted list of the occurence of different words and terms that appear in the document;

selecting a first electronic document and designating the vector of the first electronic document as a first cluster vector whereby a cluster vector is the mathematical average of all of the document vectors having similar characteristics, and assigning the first cluster vector to a first processor of the parallel processors;

selecting a second electronic document and comparing the vector of the second electronic document with the first cluster vector to determine if the second document vector has similar characteristics, and assigning the second document vector to the first cluster vector if they have similar characteristics or designating the second document vector as a second cluster vector and assigning the second cluster vector to a second processor of the parallel processors if there are different characteristics; and

selecting each subsequent electronic document and comparing the vector of each subsequent electronic document with all existing cluster vectors simultaneously on each processor having a cluster vector, and assigning each subsequent document vector to a parallel processor having the most similar characteristics or designating the subsequent document vector as a subsequent cluster vector and assigning the subsequent cluster vector to a processor of the parallel processors if there are different characteristics.

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